Application of evolutionary algorithms and classifier systems for optimisation of the operation of electric power distribution networks

1. INTRODUCTION

The analysed problem of search for optimal configurations of electric power distribution networks for changing loadings of network elements and for malfunction conditions is a multi-criteria optimisation problem. In this case the sought-after solution is the collection of Pareto-optimal solutions. Reconfiguration for restoration is a combinatorial problem involving searching an enormous space of solutions. In the article is presented the co-evolutionary algorithm using memory at the level of organised populations in the form of five subpopulations, the composition of which is changed and organised according to classifying systems’ procedures. The drawn up algorithm uses information on loadings and technical economical parameters of the analysed network. Furthermore an important objective of the method is the possibility of using information on values of reliability parameters, operating times of network elements etc.

Many approaches have been proposed to solve the restoration problem from different perspectives. For instance, researchers [1, 2] incorporated dispatcher’s experience and operating rules into an expert system to assist the dispatcher. Related investigations formulated the restoration problem as an optimization problem to minimize the number of unserviced customers [3, 4]. This problem has been approached using heuristics [5, 6, 7] mathematical programming [8], meta-heuristics (genetic algorithms, tabu search, simulated annealing) [9] and expert systems [10].

Various methods of calculation are known in the literature that enable optimisation of configurations of distribution networks in normal operating and malfunction conditions. The attempts to use heuristic search algorithms for this purpose are known. In this case the use of such algorithms for calculations for tasks is hindered by a large number of analysed network nodes. In such cases assumptions may be applied limiting the space or extent of solutions, which reduces the calculation process, but causes search for sub-optimal solutions.

Genetic and evolutionary algorithms - the benefit of application of evolutionary algorithms is the possibility of their use in large numbers of decisively variable decisions and also complex descriptions of function purpose and limiting conditions [11, 12, 13, 14, 15]. This type of method may be used to optimise the work of electric power systems consisting of a great number of elements. The possibility also exists of application to analyse the tasks of co-evolutionary algorithms, enabling the solution of multi-criteria tasks. In this case the solution searched for is a collection of Pareto-optimal solutions. These methods concern the development of specialised means of coding, reproduction methods based on domination and also use of co-evolutionary approaches. Although the obtained results have been encouraging, the majority of evolutionary algorithms still demand high running time when applied to large-scale distribution systems.

In author’s article is presented the co-evolutionary algorithm using memory at the level of organised populations in the form of five subpopulations, the composition of which is changed and organised according to classifying systems’ procedures. The elaborated method uses the theoretical background of genetic-based machine learning systems. The method shows the ability to collect experience on the base of information on faults, occurred or simulated in the power distribution systems. In the elaborated method the decisive variables, essential from the network operation reliability point of view, described with the use of fuzzy sets theory. The result of the works performed is the drawing up of an effective method enabling the rapid designa-
tion of substitute network configurations, also for very complex network structures. The process of creating a collection of classifiers describing the substitute network configuration was performed by the author supported by the theoretical genetic basics of self-teaching system. The calculations performed for the mapped real system of the medium voltage municipal distribution network have given satisfactory results, confirming the adequate direction of the research. On the base of the results obtained so far the authors assume that the results can be further used in creation of decisive procedures for complex power electric systems management, taking the fault operation states into special consideration. Cooperation of the evolutionary algorithm with the classifier system enables significant reduction of the classification time (reduces the iterative calculation process on average by 40 %), which is significant from the practical point of view in the application of this method in current systems of distribution network operation management. The application of a classifier system to the analysed task also enables improvement of the effectiveness of the performance process of designating the scenario of the substitute network configurations. The drawn up method using the co-evolutionary algorithm with memory and population level enables the search of the optimal configuration of distribution networks for normal and malfunction conditions. The proposed procedure for the creation of classifiers enables a uniform record of communications describing normal and malfunction statuses of network operation. The application to the analysed task of co-evolutionary algorithm with memory managed by the drawn up classifying system is proposed. Calculations performed for actual distribution network gave positive results. Results obtained in the form of drawn up procedures creating the most effective configuration of network appliances operation, may be used as an element of large, very complex information systems used in electric power distribution networks.

2. THEORETICAL BASES OF THE PROPOSED METHOD

The co-evolutionary algorithm applied to the analysed task creates five subpopulations, each of which is evaluated on the basis of another application function. After making a succession (supplementation of population with new elements) and by repeated reproduction, these populations are combined, and then connected, and then again divided so that each population elements may reach any population. The sought-after solution is the collection of pareto-optimal solutions.

To encode the individuals representing various network configuration variants in a form of a sparse graph, the bequest of chromosomes in the form of a vector of inversion has been assumed. Each component of the vector of inversion, corresponding to the number of the graph node, is equal to the number of the supplying node. A well-known roulette selection method on the remaining fractional part has been used as a selection method. Two specialised reconfiguration operators have been used in the algorithm to create new solutions (crossover probability \( p_k =0.95 \), mutation probability \( p_m =0.15 \)). In order to create new solutions, original operator reconfiguration is applied, the detailed description of which is contained in work [17].

Following criteria have been assumed substantial for the optimisation problem of post-fault network configuration:

\[
\min_{x \in S} F(x) = \{f_1(x), f_2(x), f_3(x), f_4(x), f_5(x)\}
\]

where: \( F(x) \) - vector of function of criterions, \( S \) - set configuration of nets.

- minimisation of the number of switching activities leading to obtaining a substitute network configuration:

\[
f_j(x_j) = \min(n_j - n_0) \quad \text{where} \quad j = 1, 2, ..., m
\]

where: \( x_j \) – vector containing information on the \( j-th \) variant of the distribution network configuration, \( m \) – number of solution variants, \( n_j \) – number of switching activities, \( n_0 \) - number of switching activities in the basic configuration.
- minimisation of the undelivered power value:

\[ f_2(x_j) = \min \{ \max (1 - p_i) \} \]

(3)

where: \( q_i = 1 - p_i \) - unreliability factor of the supply circuit of the \( i \)-th user node, \( p_i \) - unreliability factor of the supply circuit of the \( i \)-th user node.

- minimisation of the voltage deviation in the network nodes:

\[ f_3(x_j) = \min \{ \max (U_i / U_N \cdot 100) \} \]

(4)

where: \( U_N \) – distribution network nominal voltage, \( U_i \) – voltage value in the \( i \)-th user node of the network,

- minimisation of the technical losses in the distribution systems:

\[ f_4(x_j) = \min \{ \sum_{i=1}^{g} (\Delta P_i + k_e \cdot \Delta Q_i) \} \]

(5)

where: \( g \) – number of sections being loaded in the given variant of network configuration.

- minimisation of the power load degree coefficient of the found group of the most loaded network elements:

\[ f_5(x_j) = \min \{ \max [(\sum_{i=1}^{n} P_{\max,i}) / n_j] \} \]

(6)

where: \( f_5(x_j) \) - the value of this function defines the value of the loading coefficient of the most heavily loaded elements in the routes of the power supply network nodes, \( n \) - the number of the most heavily loaded network elements, \( n_j \) - the number of elements of group.

The assumed membership functions used for the main variables description have been defined as follows:

\[ u_i(x) = \begin{cases} 1, & \text{if } f_i(x) \leq f_i^{\min} \\ \left( \frac{f_i^{\max} - f_i(x)}{f_i^{\max} - f_i^{\min}} \right), & \text{if } f_i^{\min} < f_i(x) \leq f_i^{\max} \\ 0, & \text{if } f_i^{\max} < f_i(x) \end{cases} \]

(7)

The values of the function describing particular criteria considered in the optimisation model in the application of normalisation are contained within the range 0÷1.

The calculations of following limiting conditions are accepted:

- not exceeding permissible loadings of network elements,
- not exceeding permitted voltage drops in network nodes,
- fulfilment of technical conditions of supply of network nodes.
For the purpose of the applied management, the classifying system containing formation and communications assessment procedures evolutionary algorithm memory is adapted. The classifier is assigned the composition rule [17]:

\[
\text{classifier} ::= \text{condition} : \text{action/communication}
\]

The following principles are introduced in the application of the classifying system:

- communication describing examined condition of network contains a list of power values needed in network nodes and additionally possible list with numbers of damaged elements and elements of the overloaded:

\[
\text{communication} ::= (\text{loading of network nodes})
\]

- Classifiers were composed of condition and performed action, assigned to them as follows:

\[
\text{classifier} ::= \text{loading of network nodes}: \text{network configuration}
\]

The author drew up the original procedures of creating communications and assessment of classifiers. The conformity of the communication with the conditions of classifiers is specified on the basis of comparison of loadings of network nodes in communication with loadings of nodes recorded in given classifier with acceptance of certain differences (accepted permissible differences at level of 15 %).

The principle was accepted that from classifiers, which conform (or frequently conform) to communication (recording network status) information is collected on network configurations (recorded in action of classifier). These configurations are connected as subpopulation elements, which then form the co-evolutionary algorithm. At the recording of the configuration to the subpopulation of the co-evolutionary algorithm it is checked whether particular network nodes supply routes are correct. Checking the correctness of supply routes of network nodes consists of checking whether in the given route that there is no occurrence of overloaded or damaged elements. If malfunctions occur an attempt is made to repair the route with use of repair algorithm. Detailed conformity of the given classifier with the communication is defined with the aid of details function, which enables the calculation of the number of correct routes in given classifier, which did not require an application of correction algorithm. After the search for the classifiers conforming to communication, followed the assessment of the so-called offer of these classifiers. The classifier with the highest offer generated the next communication and the process proceeded further.

Performance of the process of creation of communications enables search in the collection of classifiers for information assisting the creation of five subpopulations, which then create the co-evolutionary algorithm. The classifier, which at the given the stage of creation of communications reports the best offer is assigned an award. Simultaneously its value of application is reduced by the value of the reported offer. The winning classifier offer increases the value of application of the remaining active classifiers proportionally to the offers reported by them. The effective height of offers is calculated as follows [16, 17]:

\[
S_i(t+1) = S_i(t) - c_{bid} \cdot S_i(t) - c_{tax} \cdot S_i(t) + r(t)
\]

\[
B_i = c_{bid} \cdot (e_{bid1} + e_{bid2} \cdot Sp_i) \cdot S_i
\]

\[
EB_i = c_{bid} \cdot (e_{bid1} + e_{bid2} \cdot Sp_i) \cdot S_i + e_{br}
\]

where: \( B_i \) - bid value of the \( i \)-th classifier, \( EB_i \) - effective bid value of the \( i \)-th classifier, \( Sp_i \) - specificity of the \( i \)-th classifier, \( S_i \) - strength of the \( i \)-th classifier, \( c_{bid} \) - investment coefficient \( (c_{bid}=0.1) \), \( e_{bid1}, e_{bid2} \) - coefficients of the classifier linear specificity function \( (e_{bid1}=0.65, e_{bid2}=0.35) \), \( e_{br} \) - random value generated with the use of a normal distribution generator, \( c_{tax} \) - turnover tax coefficient \( c_{tax}=0.01 \), \( r \) - coefficient of reward paid for the best classifier \( r=2 \).
Classifiers’ assessment procedures performed the process of checking classifiers with regard to the information they contain facilitating the search for solutions of the analysed task. In calculation procedures classifiers are accepted on the basis of source information [14, 15, 16, 17], and own examination of following values of significant parameters of algorithm:

- number of classifiers in population \( n = 100 \),
- standard deviation of a bid \( \sigma_{bid} = 0.075 \),
- investment coefficient \( c_{bid} = 0.1 \),
- tax coefficient \( c_{tax} = 0.01 \),
- coefficients of specificity rule linear function \( b_{bid1} = 0.65, b_{bid2} = 0.35 \),
- evolutionary algorithm parameters: crossover probability \( p_k = 0.95 \) mutation probability \( p_m = 0.15 \),
- coefficient of reward for the best classifier \( r = 2 \),
- crowding factor for population of classifiers \( c_s = 3 \).

The author applied cooperation of the evolutionary algorithm with the local search algorithm, which in this instance was the cycles and penalties algorithm. The cycles and penalties algorithm method is applied in the optimisation of dispersing power flows in electric power networks. Its main task is the minimising of technical losses through the optimisation of network configurations for the given network loading. For the purpose of applying this method to the designation of optimal post-malfunction network configurations the author introduced two modifications, consisting of limitation of the process implemented with its assistance to the area affected by the malfunction consequences. The introduction of this adaptation action did not change the principal assumptions of this method.

The first modification introduced regard in the formation stage of the list of reserved elements (on the basis of which so-called successive network cycles are created and considered) only for those network arcs, which form cycles containing network nodes deprived of power supply as a result of malfunction. The second modification concerns the use as a criteria function, in the classic form the technical losses arising from the considered network cycle are calculated.

The proposed hybrid algorithm is typified by the characteristic that in the first calculation stage it is used as the previously described evolutionary algorithm, which searches the collection of points in seeking the solution area, representing promising regions of this area. In the second part of the calculation process however the local search convergent algorithm is used, which using the previously designated points (in the form of alternative network configurations) designates the collection of best possible substitute network configurations capable of application (for the existing work conditions of that network). The collection of points represents promising regions of the area of permissible solutions obtained by the registration of 15 % of solutions contained in populations (which the evolutionary algorithm worked on) after performance of the specified number of iterations. Through this the number of performed iterations resulted from the testing of value changes of the best-obtained solutions in successive iterations.

The calculation process with the participation of the evolutionary algorithm was interrupted after confirmation of lack of improvement in application of the best solutions in 40 successively executed iterations. The population from which was chosen the 15 % best solutions (as a collection of start points for the local search algorithm) was the population after the performance of the iteration, in which the final improvement was observed in application values of the best solution during the performance of the first stage of calculations.
The proposed hybrid algorithm may also be used as a method based on cooperation of how evolutionary algorithm with the classifier system. The block diagram of the applied calculation algorithm is shown in Fig. 1.

3. **CALCULATIONS FOR THE SELECTED SYSTEM OF THE DISTRIBUTION NETWORK**

The results of calculations for the separated electric power distribution network system are presented in the point below, the accompanying diagram and graph are shown in figures 2 and 3. It is assumed that the breakdown status of the analysed distribution network occurred on the line between supply node 6 and distributor node 9, which is marked on the graph of the analysed network. In the calculations a replacement network configuration is sought with the use of the evolutionary algorithm.

The principal objective of the search was to seek the postbreakdown distribution network configurations supplying the greatest number of reception nodes.
The communication describing network malfunction status is described as follows:

(list with powers required by nodes – PA/PN) + additional list of damaged elements

where: PA - active power in a network node, PN - Rated active power power in a network node

\[
\left( \frac{P_{A1}}{P_{N1}} = 0.9, \frac{P_{A2}}{P_{N2}} = 0.4, \frac{P_{A3}}{P_{N3}} = 0.6, \frac{P_{A4}}{P_{N4}} = 0.4, \frac{P_{A5}}{P_{N5}} = 0.6, \frac{P_{A6}}{P_{N6}} = 0.9, 1.1 \ldots \right) + (6 \_9)
\]
Fig. 2. Diagram of analysed distribution network

Fig. 3. Graph of analysed distribution network
For example in the first stage of the classifier communications formation process shown in table 1. In column concerning network configuration recorded in inversion vector only initial and final elements of this vector are recorded. After the process of creating communications, follows the assessment of the produced classifiers, which are subject to assessment of this usability to solve the analysed task. In the result of performance of process of creation and assessment of communications performed in the first stage as classifier with the best offer is designated classifier number 1 (table 1). This classifier served the creation of the communication of a further process of creation of classifiers. The further process of formation of classifiers is by-passed with regard to the length of the article.

As a result of the performance of the process of formation and assessment of active classifiers, information was obtained which serves to create five subpopulations being used by the co-evolutionary algorithm. Each subpopulation was assessed on the basis of another application function (dependencies 5 to 9). The sought-after solution is the collection of pareto-optimal solutions. The course of the process of searching for the best solutions in particular subpopulations is shown in figure 4.

Table 1. Found active classifiers

<table>
<thead>
<tr>
<th>Nr</th>
<th>Active classifiers</th>
<th>Bid and Effective Bid</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>(PA1/PN1 =0.93, PA2/PN2 =0.45, PA3/PN3 =0.65, PA4/PN4 =0.44, PA5/PN5 =0.65, PA6/PN6 =0.92, PA6/PN6 =0.89…)</td>
<td>B1 = 0,919, EB1 = 0,940</td>
</tr>
<tr>
<td>2.</td>
<td>(PA1/PN1 =0.83, PA2/PN2 =0.64, PA3/PN3 =0.63, PA4/PN4 =0.54, PA5/PN5 =0.76, PA6/PN6 =0.89, PA6/PN6 =0.91…)</td>
<td>B2 = 0,939, EB2 = 0,937</td>
</tr>
<tr>
<td>3.</td>
<td>(PA1/PN1 =0.87, PA2/PN2 =0.74, PA3/PN3 =0.56, PA4/PN4 =0.64, PA5/PN5 =0.64, PA6/PN6 =0.93, PA6/PN6 =0.92…)</td>
<td>B2 = 0,827, EB2 = 0,840</td>
</tr>
</tbody>
</table>

The proposed algorithm using memory of the population level is typified with a short time of designating the following configuration of complex distribution networks. In figures 5 and 6 is shown an example comparison of the course of calculations in chosen subpopulations (no. 3 and 4) for variant with random generation of initial population and for variant with population with formation in which is used information from the collection of classifiers.
Fig. 4. Changes of the best solutions during calculations in subpopulations 1-5 – a) and changes of average application of subpopulation 1-5 – b)

As the solution of the analysed task is received the best network configurations in particular subpopulations, this information is shown in table 2.
Fig. 5. Example of best solutions fitness waveform in subpopulation number 3
Fig. 6. Example of best solutions fitness waveform in subpopulation number 4

Table 2. Information on collections of found solutions

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Results for subpopulations no. 1</th>
<th>Results for subpopulations no. 2</th>
<th>Results for subpopulations no. 3</th>
<th>Results for subpopulations no. 4</th>
<th>Results for subpopulations no. 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimisation of the number of switching activities leading to obtaining a substitute network configuration</td>
<td>$f_1(x) = 4$ ( u_1(x) = 0.893 )</td>
<td>$f_1(x) = 8$ ( u_1(x) = 0.671 )</td>
<td>$f_1(x) = 7$ ( u_1(x) = 0.707 )</td>
<td>$f_1(x) = 10$ ( u_1(x) = 0.641 )</td>
<td>$f_1(x) = 12$ ( u_1(x) = 0.619 )</td>
</tr>
<tr>
<td>Minimisation of the undelivered power value</td>
<td>$f_2(x) = 0.998031$ ( u_1(x) = 0.896 )</td>
<td>$f_2(x) = 0.998381$ ( u_1(x) = 0.998 )</td>
<td>$f_2(x) = 0.998152$ ( u_1(x) = 0.943 )</td>
<td>$f_2(x) = 0.997752$ ( u_1(x) = 0.790 )</td>
<td>$f_2(x) = 0.998261$ ( u_1(x) = 0.985 )</td>
</tr>
<tr>
<td>Minimisation of the voltage deviation in the network nodes</td>
<td>$f_3(x) = 2.23%$ ( u_1(x) = 0.647 )</td>
<td>$f_3(x) = 1.22%$ ( u_1(x) = 0.752 )</td>
<td>$f_3(x) = 1.18%$ ( u_1(x) = 0.765 )</td>
<td>$f_3(x) = 1.31%$ ( u_1(x) = 0.734 )</td>
<td>$f_3(x) = 1.22%$ ( u_1(x) = 0.752 )</td>
</tr>
<tr>
<td>Minimisation of the technical losses in the distribution systems</td>
<td>$f_4(x) = -2895$ kW ( u_1(x) = -0.635 )</td>
<td>$f_4(x) = -2679$ kW ( u_1(x) = -0.667 )</td>
<td>$f_4(x) = -2675$ kW ( u_1(x) = -0.670 )</td>
<td>$f_4(x) = -2561$ kW ( u_1(x) = -0.740 )</td>
<td>$f_4(x) = -2654$ kW ( u_1(x) = -0.682 )</td>
</tr>
<tr>
<td>Minimisation of the power load degree coefficient of the found group of the most loaded network elements</td>
<td>$f_5(x) = 0.669$ ( u_1(x) = 0.743 )</td>
<td>$f_5(x) = 0.584$ ( u_1(x) = 0.886 )</td>
<td>$f_5(x) = 0.577$ ( u_1(x) = 0.898 )</td>
<td>$f_5(x) = 0.771$ ( u_1(x) = 0.669 )</td>
<td>$f_5(x) = 0.544$ ( u_1(x) = 0.955 )</td>
</tr>
</tbody>
</table>

Fig. 7. Graph of distribution network with changes in configuration marked

The best solutions obtained in particular subpopulations are joining to the collection of subpopulation of classifiers. For example the network configuration obtained for subpopulation 3 is shown in figure 7. The final choice of solution variant depends on the operator managing the work of the electric power distribution network.

4. Conclusion

The result of the works performed is the drawing up of an effective method enabling the rapid designation of substitute network configurations, also for very complex network structures. The method drawn up may be used in current systems managing the work of distribution networks to assist network operators in taking decisions concerning connection actions in supervised electric power systems. The process of creating a collection of classifiers describing the substitute network configuration was performed by the author supported by the theoretical genetic basics of self-teaching system. Classifiers may be created (for analysed network structure) for the most probable break down situations, which arise from regarding the stage of choice of the simulated break down situations (in the analysed network) reliability characteristics and the usage durations of network elements.

The drawn up method using the co-evolutionary algorithm with memory and population level enables the search of the optimal configuration of distribution networks for normal and malfunction conditions. The proposed procedure for the creation of classifiers enables a uniform record of communications describing normal and malfunction statuses of network operation. The application to the analysed task of co-evolutionary algorithm with memory managed by the drawn up classifying system is proposed. Calculations performed for actual distribution network gave positive results. The drawn up algorithm may be used for formation of decision procedures in the management of complex distribution networks with particular regard to operation in malfunction statuses. The method may be used in systems managing current operation of distribution networks to aid the work of operators supervising electric power systems.
Summary:

The problem of optimising the configuration of electric power distribution networks during changing loadings and in malfunction conditions of the network is a task of multi-criteria optimisation. In the article is presented the co-evolutionary algorithm with memory at the population level, enabling the search for pareto-optimal solutions such as are in the analysed task of network configurations. The drawn up method is used in the organisation of evolutionary algorithm memory uses the theoretical bases of classifying systems. The method presented in the article enables effective search of optimal configurations of distribution networks for various network loadings and also network malfunction conditions.

5. REFERENCES


